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Image Annotation and Retrieval Using Dual Classifier Formulation

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Abstract: *Automatic image annotation is a difficult and highly relevant machine learningtask.Re-centadvanceshavesignificantlyimprovedthestate-of-the-art inretrievalaccuracy withal-gorithmsbasedonnearestneighborclassification incarefullylearnedmetric spaces. Butthis comesat apriceofincreasedcomputationalcomplexityduringtrainingand testing .WeproposeFastTag,anovelalgorithmthatachievescomparableresultswithtwosimplelinearmappingsthat areco-regularizedinajointconvexlossfunction. The lossfunctioncanbeefficientlyoptimized inclosedformup-dates,whichallowsusto incorporatealargenumberofimagedescriptorscheaply.Onseveralstandard real-worldbenchmark data sets, wedemonstrate that FastTagmatches thecurrentstate-of-the-artintaggingqual-ity,yetreduces the trainingand testingtimesbyseveralorders ofmagnitudeand haslowerasymptoticcomplexity.*

Key Words: *Image Annotation, Asymptotic complexity, AutomaticImageAnnotation(AIA), TranslationModel(TM), continuous-spacerelevancemodel(CRM)*

I. INTRODUCTION

Withtherapidexplosionofimagesavailablefromvariousmultimediadevices,effectivetechnologiesfororganizing,searchingand browsingtheseimagesareurgentlyrequiredbycommonusers.Ideally,thoseimagesshouldbeindexedbysemanticdescriptionssot hattraditionalinformationretrievaltechniquesmaybeadoptedforpreciseimagesearch.However,asitisimpossibletomanuallyan notatesomanyimages,automatic imageannotation(AIA)mightbeapromisingsolution.

ThegoalofAIAistoautomaticallyassignsomekeywordstoanimagethatcanwelldescribethecontentinit.Figure1illustratesatypic alsystemofautomatic imageannotation.Givenanimagecollectionandadictionaryofkeywords,acomputerassignskeywordstoea chimageautomatically.Inrecentyears,asignificantamountofresearcheshavefocusedonautomaticimageannotation.Early workb yDuygulu etal.proposethetranslationmodel(TM)totreatAIAasaprocessoftranslationfromasetofblobtokens, obtained byclusteringimage regions, toasetofkeywords.Jeonet al.putforward cross-mediarelevancemodel (CMRM) toannotateimage,assumingthattheblobsandwordsaremutuallyindependentgivenaspecific image.Subsequently,CMRMisimpr ovedthrough continuous-spacerelevancemodel(CRM)andmultiple-Bernoullirelevancemodel(MB-RM).Recently,thedualcross-mediarelevancemodel(DCMRM)whichcalculates theexpectation overwordsinapre-definedlexicon is also proposed.Inaddition,Carneiroetal.comeupwiththesupervisedmulti-classlabeling(SML),whichutilizesoptimalprincipleofminimumprobabilityoferrorandtreatsannotationasamulti-classclassificationproblem.Aslatentaspectmodels,probabilisticlatentsemanticanalysis(PLSA),latentsemanticanalysis(LSA) andlayeredpictorialstructures(LPS)havealsobeensuccessfullyappliedinautomatic imageannotation.In,Fergusetal.extendthePLSA modelbyaddingspatialinformationbasedonthevisualwords.Subsequently,MonayandGatica-Perezhaveproposedtheclassical PLSA-WORDSandPLSA-FEATURESmodels.

II. RELATED WORK

Inthissection, swereviewsomeofthepopular methodsforautomaticimageannotation.The_rstgroupofmethodsarebasedonparametrictopic models.Monay&Gatica-Perez(2004)extendtheprobabilisticlatentsemanticanalysismodel,andBarnardetal.(2003)extendthelatentdirichletallocation modeltomultimodaldata.Eachannotatedimageis modeledas amixtureoftopicsovervisualandtextfeatures.Themixtureproportionsaresharedbetweenfeaturemodes,butthetopicdistributio nsaredistinct.Thesecondgroupofmethods(Jeonetal.,2003;Lavrenkoetal.,2003; Fengetal.,2004) modelsthejointdistributionoftheimagefeaturesandthetagswithmixture models.Thethirdgroupofmethodstrainsdiscriminativ emodels,suchasSVM(Cusanoetal.,2003),rankingSVM(Grangier&Bengio,2008)andboosting(Hertzetal.,2004),topredictta gsfromimagefeatures.Whilethesemethodsachieve promisingannotationresults,their complex training processes limitthenumberof descriptors that can be incorporated.Recently proposed modelssuchas the Joint EqualContributionmodelof(Makadiaetal.,2008)andtheTagPropmodelof(Guillauminetal.,2009)relyonlocalnearestneighbo rhoodsandworksurprisinglywelldespite their simplicity. TagPropisthe current state-oftheartmethodforimageannotation.Itssuccesscanbeattributedtothreeelements:

1. Itincorporatesalargenumberofdi_erentvisualdescriptors;
2. It can betrainede_ectivelyonimageswithincompletetagsets;
3. Ittreatsraretagsspecial.AlthoughTagpropachievessuperiorperformanceonseveralbenchmarkdatasets,theO(n2)trainingandO(n)testcomplexityhinderitsapplicabilitytolargescaledatasets(whereneisthenumberofexamplesinthetrainingset).Inthiswork,weintroduceanewmodelthatincorporatesthesethreeelementsforsuccessfulannotationmuchmorecheaply.Mostexisting modelsassumethatacompletelistofrelevanttagsforeachimageisavailableattraining time.However,inpractice,thisiseitherimpracticalorimpossibleforalargetrainingset.Itismucheasiertotaganimagewithafewofthemostprominentvisualfeaturesthantoobtainthecompletelistfromatagdictionary.Toalleviatetheneedforcompletelabeling,severalexistingapproaches(Fergusetal.,2009;Schro_etal.,2007;Socher&Fei-Fei,2010)resorttosemi-supervisedapproachestoleverageunlabelledorweaklylabeleddatafromtheweb.Weadoptthesameassumptionofsparsetrainingtagsandincorporatepartialsupervisioninourwork.

III. DUO CLASSIFIER FORMULATION

In this section we introduceanewmodel for automatic image annotationfromincomplete user tags. Itjointly learns two classifierson two sources, i.e., image and text, to agree upon the list oftagspredicted for each image. Itleadstoanoptimizationproblem which is jointly convex and hasclosed form solutionsin eachiterationoftheoptimization.

IV. CO REGULARIZED LEARNING

As we areonlyprovided with an incomplete set of tags, we create an additional auxiliaryproblemandobtain two sub-tasks:
1.Training an image classifier xi -W xithatpredicts the complete tagsetfromimage features, and
2.Training a mapping yi-Byi to enrich the existingsparsetag vector yi by estimating which tagsarelikelyto co-occur with thosealready in yi.Wetrainbothclassifierssimultaneously and force their outputto agree by minimizing.

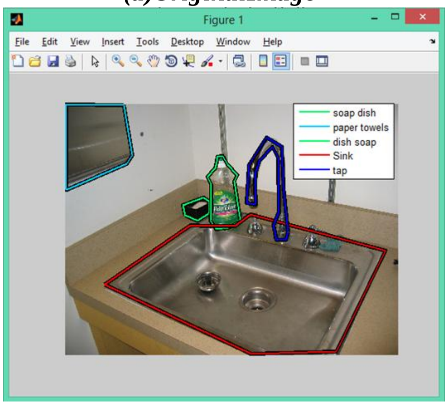
$$\frac{1}{n}\sum_{i=1}^{n}\|\mathbf{B}\mathbf{y}_i - \mathbf{W}\mathbf{x}_i\|^2.$$

Here,Byiistheenrichedtagsetforthei-thtrainingimage,andeachrowofWcontainstheweightsofalinearclassi_erthattriestopredictthecorresponding(enriched)tagbasedonimagefeatures.Thelossfunctionascurrentlywrittenhasatrivialsolutionat B=0=W,suggestingthatthecurrentformulationisunderconstrained.WenextdescribeadditionalregularizationsonBthatguidesthesolution.

V. EXPERIMENTAL RESULTS

Theoutcomeofthe DualClassifierformulationmethodisannotationofobjectinimage images.

(a)OriginalImage



(b) AnnotatingImage

ThequalityoftheResultantimagebasedonhowwelltheytrainwithoutlosinganyproperties.

VI. CONCLUSIONANDFUTUREWORK

Wepresentan image tagging method, FastTag,thatperformson-parwithcurrent state-of-the-artalgo-rithms,atafractionofthecomputationcost.Were-castasupervisedmulti-labelclassificationproblemas unlabeledmulti-viewlearning.Wedefinetwoclassi-fiers,oneforeachview ofthedata,andcoercethemintoagreementviaco-regularizationinajointlossfunction.Wetradeoffcomplexityintheclassifierswithnon-linearmappingofthe featuresand demon-stratethatsuchachoicepaysoff.FastTagiscomputa-tionallyefficientduringtrainingandtestingyetmain-tainstaggingaccuracy.It caneffectivelydeal withsparsely tagged trainingdata andrare tagsthatareoftenobstaclesinsuchlarge-scalelearningproblems.

InfutureworkWeproposeslowcomplexityandfastalgorithmforimageannotationusingdualclassifierformulation.Itiscanbealso applicablefortheVideotagging.

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